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A novel and direct ecological risk assessment index for environmental degradation based on response curve approach and remotely sensed data

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ABSTRACT

Ecosystems are at risk of environmental degradation by the intensification of human activities and climate change over the world. This manuscript aims to present a systematic and direct methodology for abiotic risk assessment. In this study, a novel ecological risk assessment index called "performance relative severity index" (PRS) was developed to directly identify the risk of ecosystem collapse due to abiotic stress. The index is acquired by calculating the degree of deviation from performance of ecosystems to optimum performance that caused by the degradation of environment. First, the key abiotic variables distinguishing ecosystems should be identified. Second, the response curve indicating the relationship between ecosystem performance and key abiotic variables should be constructed. Due to the lack of the information on the response curve for some regions, the minimum and maximum points of optimum and tolerance range, defining the response curve of ecosystem to abiotic variables, should be acquired. The minimum and maximum optimal points were obtained through the relationships between the index derived from remotely sensed data and abiotic variables, and the minimum and maximum tolerance points were acquired by the relationships between the occurrence of ecosystem and its environment. Based on the response curve of ecosystem to abiotic variable, the performance of ecosystem to current abiotic variables were available. Finally, the PRS was acquired through calculating the ratio of the change in the performance of ecosystems caused by environmental degradation to the change that would cause an ecosystem to collapse. The proposed methodology was applied to calculate the PRS of the natural forest regarding temperature in Xishuangbanna, a biodiversity hotspot located in Southwestern China. The results show that the suitable bioclimatic zone for ecosystems in Xishuangbanna would be shifted to higher altitude region under global warming. Considering ecosystems are always lag behind the effects of climate changes, these conversions indicate potential heat-stress to the natural forests of lowland in Xishuangbanna due to significantly rising temperatures in the future.

1. Introduction

Ecosystems provide irreplaceable ecological services for human and organism, which play an important role in maintaining biological diversity (Pecl et al., 2017). Environment is the part of ecosystems that provides abiotic resources such as heat, water and minerals for organisms (Begon et al., 2006; Braak and Looman, 1986; Odum et al., 1971). Environmental degradation, such as heat and chilling condition, drought, acid, soil erosion and pollutions, may pose stress on ecosystems and cause disruption to the ecological balance of ecosystems (Malekmohammadi and Rahimi Blouchi, 2014). Therefore, when environment is degraded, the quality of environmental niche for organisms may be altered and the ability of ecosystem to sustain its native biota will be diminished (Keith et al., 2013).

With global climate change and severe human disturbance, natural environment around the world have suffered substantial degradation, potentially putting great stress on ecosystems (Cardinale et al., 2012; MA, 2005). Assessing the abiotic risks to ecosystems is the first step to protect ecosystems from the environmental degradation and raise public awareness of ecosystem conditions (Malekmohammadi and Rahimi Blouchi, 2014). Environmental monitoring and ecological risk assessments (ERAs) are used to estimate the properties of the environment that are susceptible to stressors of concern to support decision making (Ii, 2002). Previous studies of ecosystem risk assessment mainly

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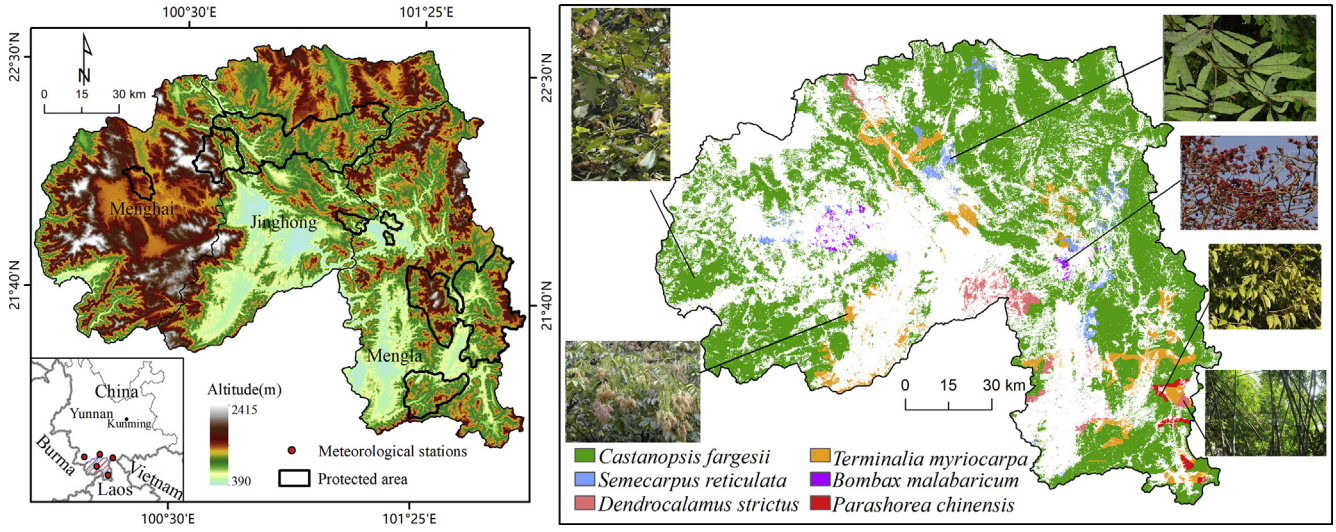

Fig. 1. The location of Xishuangbanna and meteorological stations (left), as well as the occurrence of natural forests in 2015 (right).

focused on multimetric indices such as the assessment in US Environmental Protection Agency (EPA, 1998), and these indicators are often presented by indices or scores that obscure the actual condition of the environment (Ii, 2002). Therefore, ERAs have been disjunct in practice (Chen et al., 2013; Ii, 2002). These may offer an opportunity to further explore the ecological risk assessment for abiotic stress.

Actually, each species is featured with its own ecological response to different environmental factors which can be described with optimum range and tolerance range (Odum et al., 1971). The optimum range has been defined as an range along a gradient of an environmental resource where a species population is near or at its maximum (Hearnshaw and Hughey, 2012), and tolerance range is characterized by the ability of a species to survive along the environmental resource gradient (Niinemets and Valladares, 2008; Shelford, 1913). The tolerance/optimum range of a species is the breadth between its minimum tolerance/optimal point and its maximum tolerance/optimal point along an environmental resource gradient (Hearnshaw and Hughey, 2012). With the consideration of multiple limiting factors, the long-term survival (or inhabitance) of a species requires that all of its tolerance ranges reside beyond the environmental resource gradients found in (or along) the ecosystem assessed (Hearnshaw and Hughey, 2012). When environmental condition is beyond to the tolerance range, the organisms of ecosystems would be vulnerable, whereby further degradation of environment in the future may lead to their local extinction or migration (Niinemets and Valladares, 2008). Hence, the concept of response curve to environment is intimately linked to vulnerability of ecosystems and allows the ecological risk assessment (Hearnshaw and Hughey, 2012).

The abiotic factor poses no threat to ecosystems when environmental variable locates in the optimum range, and the environment would cause lethal effects on ecosystems when abiotic variable is beyond tolerance range (Townsend et al., 2009). The risk to ecosystems caused by abiotic degradation increases with the increasing deviation from the optimum range (Begon et al., 2006). The risk of abiotic degradation to ecosystems can be assessed by calculating the degree of deviation from performance of ecosystem to its optimum performance in response curve. Therefore, a novel and direct ecological risk assessment index, called “performance relative severity index” (PRS), was developed in this paper through measuring the proportional progress of ecosystems’ performance on a trajectory to collapse (Rodríguez et al., 2015). The proposed index describes the relative severity of degradation for environmental variables. The higher the value of PRS, the higher the ecosystem risk caused by abiotic degradation.

Theoretically, the response curve to environment should be developed based on experiments and ground-based observations (Townsend et al., 2009). However, given the broad extent of ecosystems and the limits of manpower and material resources (Tan et al., 2017), it is very hard to acquire the response curves to environment of all ecosystems. Remotely sensed data, such as vegetation indices, provide realistic information on ecosystem dynamics, including water quality changes, land cover changes and vegetation disturbances (de Araujo Barbosa et al., 2015; Stereńczak et al., 2017). Satellite data have been successfully used to study the response of ecosystems to the environment, providing potential data for developing the response curves (Hawinkel et al., 2015; Pettorelli et al., 2005). The relationship between occurrence and environment are widely used to acquire the tolerance range (Virtanen et al., 2006). In this paper, satellite data and relationship between occurrence and environment were applied to construct the response curve of ecosystem to the environment where information of the response curve is limited.

Xishuangbanna is one of the world’s 34 biodiversity hotspots (Myers et al., 2000). Many valuable and rare species are clustered in its natural vegetative ecosystems (Zhang and Cao, 1995). The remaining forests in Xishuangbanna is limited distributed due to its transitions to rubber plantations and tea gardens in the past (Li et al., 2006). Although the degradation of natural forest has slowed down, previous studies have indicated that bioclimatic strata in Xishuangbanna would be substantially affected by climate changes (Zomer et al., 2014; Zomer et al., 2015). Great attention should be paid to the effects of climate changes on the last surviving natural forest in Xishuangbanna and the proposed method was implemented to assess the risk of abiotic degradation to natural forest during different period.

Therefore, the main objectives of this study were to: (1) provide a systematic and direct methodology for ecological risk assessment; (2) test the feasibility of constructing the response curves of ecosystem to environment by remotely sensed data and ancillary data; (3) identify the risk of temperature changes to natural forests in Xishuangbanna and provide corresponding measurements.

2. Study area

Xishuangbanna (99°56′-101°50′E, 21°08′-22°36′N, 19124 km^2) is located in Yunnan Province of Southwestern China, which includes Jinghong, Menghai and Mengla and borders Laos and Burma (Fig. 1). Xishuangbanna lies in the transition zone from the Eastern Himalaya to Southeast Asia, consisting of hills, middle and low mountains (Zhu et al., 2015). It locates in a transition zone between tropical and subtropical climates. The annual mean temperature varies from 21.7 °C to 15.1 °C (Zomer et al., 2014). The hottest month is June with a mean

temperature of 17.9 °C to 25.3 °C, and the coldest month is January with a mean temperature ranging from 8.8 °C to 15.6 °C. The annual precipitation ranges from 1193 mm to 2491 mm, of which more than 80% falls are distributed during the rainy season from May to October (Zhu et al., 2015). The region is characterized with three main soil types: laterite soils developed from siliceous rocks, lateritic red soil from the rock substrate of sandstone and soil from rock substrate of hard limestone of Permian origin with a pH of 6.75 (Zhu et al., 2015).

The complex topography and climate in this area have resulted in it being one of the global biodiversity hotspots (Myers et al., 2000; Zhu et al., 2015). Natural forest in this region provides valuable habitats for rare vegetation species and animals, which play an important role in biodiversity conservation (Xu et al., 2012). The natural forest here can be divided into six categories: *Bombax malabaricum*, *Castanopsis fargesii*, *Terminalia myriocarpa*, *Parashorea chinensis*, *Semecarpus reticulata* and *Dendrocalamus strictus* (Fig. 1). *Castanopsis fargesii* is widely distributed across this region, while *Bombax malabaricum* is restrictedly distributed.

With climate changes, the mean annual temperatures in the study area have significantly increased and would further increase by almost 2 °C in the 2060s at the RCP 2.6 and more than 3 °C at the RCP 8.5 (IPCC, 2014). On the other hand, rainfall and radiation in this region has remained unchanged in the past, and would slightly increase in the future (IPCC, 2014). The significant increase of temperature would shift the bioclimatic zones of Xishuangbanna in the future, and these changes would undoubtedly lead to negative impacts on biodiversity conservation and effectiveness of ecosystem management (Zomer et al., 2014; Zomer et al., 2015). The increased temperature may cause potential drought and heat stress to ecosystems, which is the most likely environmental factors that threating the natural forest in Xishuangbanna (Allen et al., 2010; Loehle et al., 2016; Malcolm et al., 2006). Therefore, mean annual temperatures was considered as one of the key abiotic variables that determine the status of natural forests of Xishuangbanna in the future. And this study take the risk resulting from temperature changes to natural forest in Xishuangbanna as an example.

3. Methods

3.1. Data sources and processing

The map of forest type exhibits the spatial distribution of forest which is the basis of assessing risk to natural forest. In this study, to meet the requirements of assessment, the forest map was produced by fusing data from ChinaCover (Lei et al., 2016) and the Vegetation Map (Vegetation Map of the People's Republic of China (1:1,000,000)) based on the method proposed by Lei et al. (Fig. 1) (Editorial Committee of Vegetation Atlas of China, 2007; Lei et al., 2016). The forest types in the forest map are similar to the ecosystems in Vegetation map representing the key or main species of forest and the environment suited for this forest (Tan et al., 2017).

The occurrences and its corresponding bioclimate of each natural forest in Xishuangbanna were collected through Global Biodiversity Information Facility (GBIF) and Worldclim to acquire the range of temperature tolerance (Fick and Hijmans, 2017; GBIF, 2018). Normalized differential vegetation index (NDVI), widely applied for monitoring the status of vegetation, was used in this study to acquire the range of temperature optimum of natural forest in Xishuangbanna (Wylie et al., 2008). NDVI was obtained from a 16-day composited Terra MODIS 250 m NDVI (2000–2015) and smoothed to remove residual clouds with a S-G filter (Bian et al., 2010).

The risk of environmental degradation to ecosystems in the past (1965), present (2015) and future (2060s) should be assessed to identify the trends of risk according to the 50-year time frame in the IUCN Red List of Ecosystems protocol (Keith et al., 2013). Therefore, the meteorological data in past, present and future should be acquired. Meteorological stations within and nearby this region were derived from China Meteorological Data Service Center (CMDC) including meteorological stations in Lancang, Jinghong, Simao, Mengla and Jiangcheng (Fig. 1). These meteorological stations were spatially interpolated to acquire the surface of annual mean temperature in the past and present based on Anusplin, which is one of the common and accurate method that considering the impacts of terrain during the Meteorological Spatial Interpolation (Appendix S1) (Tan et al., 2016). The interpolated surfaces of annual mean temperature accompanying the NDVI time series were also acquired by the interpolation method of Anusplin.

Future climate condition was provided by the Beijing Climate Center Climate System Model (bcc_csm1_1_m) (Wu et al., 2013), participating in Coupled Model Intercomparison Project Phase 5 (CMIP5) and possessing a good capability in predicting climate in East Asia (Xiao-Ge et al., 2013). Four representative concentration pathways (RCPs) or emission scenarios (low: RCP2.6, medium: RCP4.5 and RCP6.0; and high: RCP8.5) were used in predicting future temperature (Appendix S1) (IPCC, 2014).

3.2. The response curve to the environment

The response curve of ecosystem to environment indicates the performance of ecosystems along with environmental resource gradient (Townsend et al., 2009). Response curve to the environment varies with abiotic factors and the type of ecosystem (Begon et al., 2006; Heikkinen and Mäkipää, 2010). Combined with physiological response of organism to environment (Smith, 1998), the response curve of ecosystems to environment can be generally divided into the following four types (Fig. 2).

Type A indicates that organisms in ecosystems perform best at the limited range of abiotic factors, with their activity tailing off at both lower and higher levels (Fig. 2A). In the reality, the type A curve is more frequently described by asymmetric functions and the majority of abiotic variables conform to this type, such as temperature, precipitation, pH and illumination (Townsend et al., 2009). Type B indicates that a low intensity or concentration of an abiotic factor has no effects, such as most toxins and chemical pollutants. With increasing intensity,

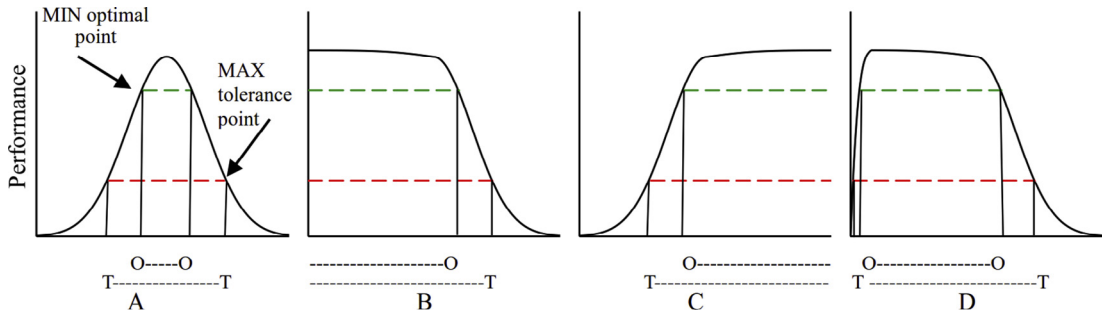

Fig. 2. Response curves illustrating the effects of a range of environmental conditions on organisms within ecosystems. T and O represent the tolerance range (red dashed line) and optimum range (green) respectively. MIN and MAX is short for minimum and maximum respectively.

environmental factors begin to cause damages to ecosystems, and a further increase can be lethal (Fig. 2B) (Begon et al., 2006). Contrary to type B, the high intensity of the environmental variables have no effects in type C. With decreasing intensity, abiotic factors begin to cause damages and a further decrease may result into collapse (Fig. 2C). These variables include the area of bog for swap, volume of water for fish and so on. Type D is similar to type B, and there is a different form of response to conditions that are toxic at high levels but essential for growth at low levels (Fig. 2D). This is the case for minerals such as Na^+, Ca^{2+} and K^+, which are necessary for organisms but higher concentration may be lethal (Townsend et al., 2009).

The PRS can be acquired based on the ratio of the change in the performance of ecosystems caused by the environmental variables to the change that would cause an ecosystem to collapse by referring to the risk assessment of environmental degradation in the IUCN Red List of Ecosystems protocol (Eq. (1)) (Rodríguez et al., 2015). The PRS directly indicates the relative severity of risk posed to ecosystems by environmental degradation. And higher PRS means that the degradation of ecosystem is more serious.

$$PRS = \frac{P_O - P_T}{P_O - P_C} \times 100\% \quad (1)$$

$$\text{response curve} = F(C, O) \quad (2)$$

where the P_O is the performance value of the response curve at the optimum points; P_C is the performance value of the response curve at the tolerance points; P_T is the performance value of ecosystem at time T. C and O in eq. (2) are the critical points of tolerance and optimum in the response curve; F is the function describing the relationship between the response curve and the two parameters (C and O).

By referring to the ecological endpoints in the IUCN Red List of Ecosystems protocol, the level of risk caused by environmental degradation can be classified into two non-threated categories (Least Concern (LC), Near Threatened (NT)), three threatened categories (Critically Endangered (CR), Endangered (EN) and Vulnerable (VU)) and one category for collapsed (CO) based on the value of PRS (Fig. 3) (Keith et al., 2013; Malekmohammadi and Rahimi Blouchi, 2014). When the value of the variable is beyond the tolerance range, the ecosystem is collapsed (CO) (Fig. 3A). When the temperature is within the favorable range, the performance of the ecosystem is optimal (OP) (Fig. 3C). For other positions, PRS would be computed by the deviation from performance of ecosystem to its optimal performance, and ecosystems are classified into different levels of risk based on the ecological endpoints in the IUCN Red List of Ecosystems protocol (Eq. (1), Fig. 3B).

The response curves can be described by the range of optimum and tolerance (Eq. (2)) (Braak and Looman, 1986). Thus, if the optimum and tolerance range of response curves and the key environmental variables are available, assessors can directly and feasibly obtain the ecological risk assessment index of abiotic stress.

3.3. Establishing the response curves by remotely sensed data

Favorable environment results in well-performed ecosystems. Conversely, a well-performed ecosystem implies favorable environment for ecosystems, and poorly-performed ecosystem indicates abiotic or biotic stresses on ecosystems. Considering the macro extent of ecosystems, the performance or status of ecosystems are usually detected by satellites (Nagendra et al., 2013). Therefore, through the performance of ecosystems derived from satellite data, we can determine whether the status of the environment is suitable for or harmful to ecosystems. NDVI, leaf area index (LAI) and biomass derived from satellite data are usually applied to identify the performance of vegetation ecosystems (Smith et al., 2014; Wylie et al., 2008). The metal density, chlorophyll and salinity derived from satellite images are used to detect the performance of aquatic ecosystems (Polonia et al., 2015).

A well-performed ecosystem can definitely imply favorable environmental conditions for ecosystems. While, hardly can we determine whether the stress is derived from environmental degradation and which abiotic factor counts when an ecosystem is poorly-performed because of the potentially synchronous influence of biotic factors. Therefore, only the optimum range was derived from the remotely sensed data. And the tolerance range was acquired based on the relationships between occurrences of ecosystems in the GBIF and its environment from the Worldclim dataset (Appendix S2) (Fick and Hijmans, 2017; GBIF, 2018).

3.4. The framework of the proposed method

The methodology can be summarized in the flowchart (Fig. 4). The whole workflow includes five steps that are described in the following:

- Identifying the abiotic variables that distinguish the ecosystems (step 1). Distinguishing the key abiotic variables that determining the status of ecosystem is the first step to implement ecosystem risk assessment. The physical stresses include the temperature, humidity, PH of soil or water and illumination. The chemical stresses include the concentration of toxins, chemical pollutants and minerals.
- Establishing the response curve (step 2). The tolerance range can be acquired by ancillary data or the relationships between the distribution of ecosystem and its environment. The optimum range can be obtained through the relationships between remotely sensed time series data and abiotic variables.
- Acquiring PRS index (step 3). With the performance of abiotic variables in the response curves, the PRS index can be obtained by calculating the ratio of the change in the performance of ecosystems caused by environmental variable to the change that would cause an ecosystem to collapse.
- Risk priorization (step 4). After acquiring PRS index of each abiotic

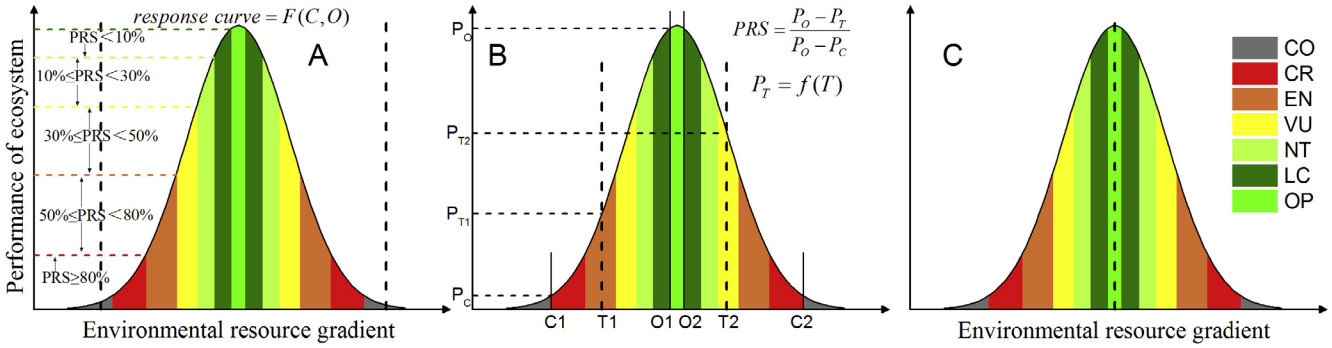

Fig. 3. The position of conditions (vertical dashed line) in the response curve of Type A. C and O represent the value of condition that lead to ecosystem collapse and optimum state of ecosystem, and T is the value of condition between them. *f* is the function describing the response curve. P is the value of performance which is the result of *f*.

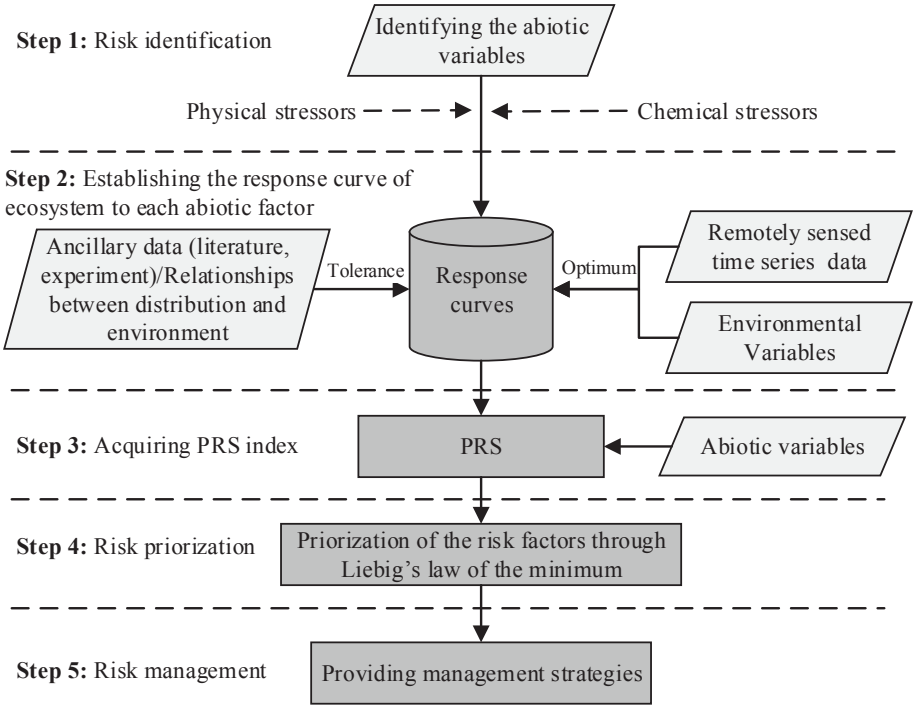
Step 1: Risk identification
Identifying the abiotic variables
Physical stressors
Chemical stressors
Step 2: Establishing the response curve of ecosystem to each abiotic factor
Ancillary data (literature, experiment)/Relationships between distribution and environment
Tolerance
Response curves
Optimum
Remotely sensed time series data
Environmental Variables
Step 3: Acquiring PRS index
PRS
Abiotic variables
Step 4: Risk priorization
Priorization of the risk factors through Liebig's law of the minimum
Step 5: Risk management
Providing management strategies

Fig. 4. The flowchart of integrating the response curves and remotely sensed data to identify the ecological risk of abiotic stress to ecosystems.

factor, they are prioritized by their importance. This can be done according to the classification of relative severity of risk based on the ecological endpoints in the IUCN Red List of Ecosystems protocol. And the high level of abiotic factor that threaten ecosystems should be prioritized. For each point or zone, the highest risk level of different abiotic factors will be assigned as final level of risk by Liebig's law of the minimum (Hiddink and Kaiser, 2005).

- Risk management (step 5). Finally, risk management strategies will be provided for high-risk zones on the basis of the risk derived from each abiotic factor.

3.5. Identify the risk of temperature to natural forests with the proposed method

Abiotic variables that distinguish ecosystem should be properly identified. An appropriate abiotic variable can represent ecosystem processes, which explicitly relates to the capacity of ecosystems to sustain its identity (Rodríguez et al., 2015). In this study, compared with other abiotic factors, the significantly increased temperature have the maximum potential in shifting the bioclimate in Xishuangbanna. Moreover, the data of temperature is easily accessible. Therefore, the temperature was regarded as one of key abiotic variable which belongs to type A (Fig. 3). As the limited of data, this study only demonstrated the case of identifying the risk of temperature changes to natural forests in Xishuangbanna with the proposed method.

Ecosystem performance (EP) of natural forests in the response curve was defined by the seasonal integrated NDVI over the growing season (May to October) according to predecessors' research (Gu and Wylie, 2010). Based on the variation of EP with mean annual temperature, the mean annual temperature, where its corresponding integrated NDVI was maximum, was assigned as the optimum temperature for each pixel (Fig. 5). Through this process, the optimum temperature of each pixel was acquired and the map of optimum temperatures was available (Appendix S3). To acquire the favorable range for each ecosystem, the statistics of the optimum temperature were computed in terms of forest type, based on the map of optimum temperatures (Appendix S4). In addition, the value at the 95% confidence interval was used in determining the optimum range because of the possible error of the forest map. The tolerance range of mean annual temperature was derived from the relationship between occurrence and environment (Appendix S2). Combined with the optimum and tolerance ranges, we fitted the response curves of each forest type to mean annual temperature with the model of temperature stress on light use efficiency (Li et al., 2012).

According to the 50-year time frame in the IUCN Red List of Ecosystems protocol (Keith et al., 2013), the PRS index of natural forests to annual temperature in the past (1965), present (2015) and future (2060s) were acquired based on the proposed method.

4. Results and analysis

4.1. The response curves of each ecosystem

According to the tolerance range of each forest (Table 1), *Bombax malabaricum* and *Castanopsis fargesii* are distributed in subtropics and tropics, characterized with wide range of tolerance. The minimum optimal point of annual temperature for *Castanopsis fargesi* is 16.03 °C which is the lowest minimum optimal point. The minimum tolerance point of tropical forests such as *Dendrocalamus strictus* forest, *Semecarpus reticulata* forest, *Parashorea chinensis* forest, *Terminalia myriocarpa* forest, are more than 18.2 °C which are featured with high value of minimum tolerance point. The minimum optimal point of *Bombax malabaricum* is 18.25 °C which is the highest minimum optimal point as it inhabits in dry-hot conditions.

The optimum and tolerance range of each ecosystem were acquired by the information of occurrences in Xishuangbanna. However, some ecosystems may also occur in other regions, and the environmental condition may tougher than that in Xishuangbanna. This may leads the optimum and tolerance range we acquired being narrower than its actual range. The optimum and tolerance range of *Terminalia myriocarpa* obtained in this study are close to and inside its corresponding value (optimum: 17.1 °C − 22.3 °C; tolerance: 13.7 °C − 26.3 °C) in the Flora of China (Tan et al., 2017; Wu and Raven, 1990), which is consistent with above points. This indicates the robustness of the proposed method in acquiring the tolerance and optimal range.

From the response curve of each forest type in Xishuangbanna, the tolerance range of forest types were overlaid as these forests were

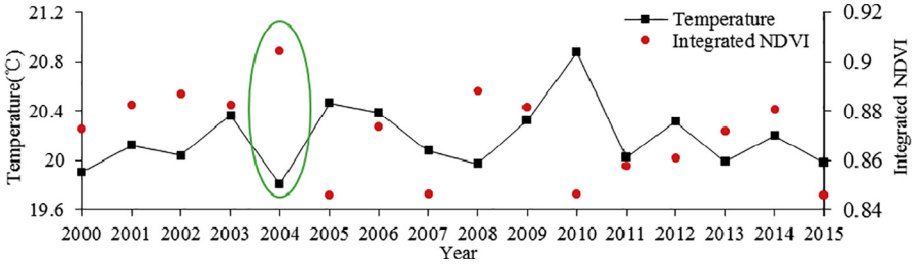

Fig. 5. The diagram of acquiring optimal mean annual temperature (green circle) with integrated NDVI.

mixedly distributed in study area, especially for tropical forests (Fig. 6). Most forests are sensitive to heat and have a high tolerance to chilling temperatures, which is consistent with the point that the response functions of organisms to temperature are negatively skewed (Niinemets and Valladares, 2008).

4.2. The PRS of natural forest to annual temperature

According to the PRS of natural forest to annual temperature during different period of time, the ecological risk initially decreased and then increased with temperature warming (Table 2). At higher emission scenarios (RCP 4.5 and 8.5), the ecological risk derived from annual temperature has significantly increased. During the period of time, the PRS of almost all forests in the present is the lowest except for *Bombax malabaricum*. Given *Bombax malabaricum* inhabits in dry-hot conditions, the PRS of *Bombax malabaricum* is the highest in the past for low temperature and lowest in the future for warmer temperature (Wu and Raven, 1990). The *Parashorea chinensis* is sensitive to climate warming for its narrow optimal range which result into a high risk derived from climate warming (Table 2).

Although, the status of overall natural forest is no-threated categories (LC, NT), the PRS of each forest in Xishuangbanna would be significantly increased with higher emission scenarios in the future. The status of ecosystem inhabiting *Parashorea chinensis*, a precious type, is VU at RCP 8.5 implying a potential stress derived from climate warming (Wang, 2004).

The spatial distribution of PRS is presented in Fig. 7 and the spatial distribution of PRS of each forest were showed in Appendix S6. The threatened regions of the past are at the high altitudes, where the temperature is lower, indicating chilling stress (Fig. 7). On the contrary, the threatened regions of the future are in the low lands where the temperature is higher, indicating heat stress (Fig. 7). With higher emission scenarios, the threatened regions in the future expand from low land to up land (Fig. 7).

4.3. Relationship between PRS and altitude

From the distribution of PRS along with elevational gradient (Fig. 8), the threatened pixels of all types are located in high altitude region during the past and present, while it is totally reverse in the future. Taking *Castanopsis fargesii* for example, in the past, the altitude of pixels whose PRS are more than 30% are above 1800 m; while in the future at RCP 2.6, the altitude of pixels whose PRS are more than 30% are under 750 m (Fig. 8). The temperature in high altitude region is lower than that in low altitude regions which indicates chilling stress for the patches located in the high altitude area during the past and present. The occurrences of natural forests in the high altitude region are rare leading to low risk in the past and present for most of natural forest, except for *Bombax malabaricum* (Fig. 8, Table 2). With climate warming, the PRS of natural forests in high altitude have significantly decreased and the PRS in low altitude have potentially increased. Under climate warming, the altitude of low value of PRS have the trend of shifting to high elevation indicating the suitable bioclimatic zone of natural forests have the potential to move to high elevation, which is consistent with previous studies (Zomer et al., 2014). In the future, with higher emission scenarios, the suitable condition of ecosystems in the future shifts to higher altitude and the value of PRS in low altitude is higher (Fig. 8).

Through the elevation of each status during different period (Fig. 9A), the mean altitude of LC increases with climate warming which indicates that the suitable bioclimatic zone of natural forest may move to the high altitude regions. From the past and present to the future, the mean altitude of threatened patches dropped a lot. This conversion implies chilling stress in the past and heat stress in the future, considering upland featured with low temperature and lowland characterized with high temperature. For each emission scenario in the future, the lower the altitude of ecosystem, the more serious its status. The area of no-threated level increased from 1965 to 2015, and then decreased in the future (Fig. 9B). With higher emission scenarios, the area of threatened level have significantly increased. In all, the area of extremely threatened level is small and natural forests in Xishuangbanna are no-threats (Fig. 9B, Table 2).

5. Discussion

With the significant environmental changes around the world, assessing the risk of abiotic degradation posed to ecosystem is necessary (Newbold et al., 2015). In this paper, a novel and direct PRS index was proposed based on the method of integrating response curves and satellite data to assess the risk of abiotic degradation to ecosystems.

Table 1
The area, optimum and tolerance range of mean annual temperature of each forest.

Forests	*Castanopsis fargesii*	*Bombax malabaricum*	*Terminalia myriocarpa*	*Parashorea chinensis*	*Semecarpus reticulata*	*Dendrocala-mus strictus*
Area (km^2)	8128.97	47.94	629.99	57.12	213.10	190.11
MINT (°C)	8.5	9.8	13.7	13.3	13.1	13.7
MAXT (°C)	25.7	27.0	26.3	25.9	25.6	26.5
MINO (°C)	16.03	18.25	18.48	18.70	18.29	18.81
MAXO (°C)	21.51	22.12	21.97	21.34	21.73	22.15

MINT and MAXT are short for minimum tolerance point and maximum tolerance point respectively. MINO and MAXO are short for minimum optimal point and maximum optimal point respectively.

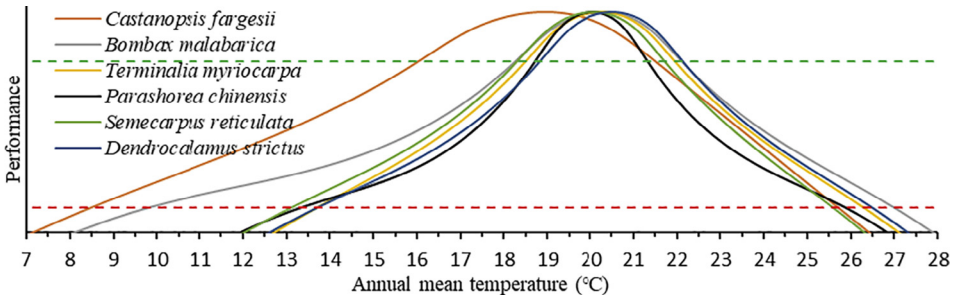
Castanopsis fargesii
Bombax malabarica
Terminalia myriocarpa
Parashorea chinensis
Semecarpus reticulata
Dendrocalamus strictus
Performance
7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28
Annual mean temperature (℃)

Fig. 6. The response curve of each natural forest in Xishuangbanna to annual mean temperature. Red and green horizontal dashed-lines are the critical points of ecosystem collapse and optimum state of ecosystem respectively.

5.1. Implications of the proposed method

5.1.1. Eliciting response curves to acquire PRS index for abiotic risk assessment

The proposed PRS index is acquired by calculating the relative severity of the degradation of ecosystem performance caused by environmental degradation, which directly indicate the abiotic risk to ecosystems. As all ecosystems have their own response curves to each environmental variable, the proposed PRS index will greatly expand the availability and generality of the abiotic risk assessment. The ecological significance of parameters in the response curves across different ecosystems is similar, which largely promoting the consistency and comparability of ecosystem risk assessment.

However, the mechanism of ecosystem's response to environment is far more complex than that described in this study. Ecosystems contain many species and organisms, which are characterized by the capacity of plasticity and adaptation (Niinemets and Valladares, 2008). The response of ecosystems to environment may be dynamic and hard to describe. Rather, ecosystems are synchronously controlled by multitude of environmental factors (Hearnshaw and Hughey, 2012). In this study, physiological responses (Fig. 2), describing the response of organisms to environment in the absence of competition and facilitation effects, were used as the response curves of ecosystems to the environment (Niinemets and Valladares, 2008). Although physiological responses are different from the realistic ecological response curve, eliciting physiological responses is an effective way to achieve the trade-off between realism and simplicity.

5.1.2. Acquiring response curves based on satellite data and ancillary data

The optimum and tolerance range defining the response curve were obtained by remotely sensed data and ancillary data in this study. Compared with other methods, satellite can provide timely and wide-ranging monitoring of the status of ecosystems where traditional methods are unavailable (Hawinkel et al., 2015). Based on the relationship between the performance of ecosystems derived from satellite data and environmental variables, we can acquire the optimum and tolerance range of response curves to the environment. However, in reality, the changes of ecosystem performance may be result from biotic stress. Hardly can tolerance range be acquired by satellite data. The relationships between environmental variables and the occurrence of ecosystems were widely used to acquire the environmental tolerance range of ecosystems (Lynch and Gabriel, 1987). Therefore, ancillary data, such as experts' experiences and the relationship between the environment and the occurrence of ecosystems, can be used to obtain the tolerance range. Combining satellite data and ancillary data provide a feasible method to acquire the response curve of ecosystems to environment where this information is limited.

However, the time of available remotely sensed data may not long enough to acquire the optimal range and natural fluctuations of ecosystems may pose effects on the optimal range acquired by remotely sensed data (Pettorelli et al., 2005). In this study, the data in the past is deficient and the satellite data during the last 16 years (2000–2015) was used to acquire the optimum range. And the optimal range we acquired only represents the optimal value in the last 16 years which may result in the status of present being slightly better than that in the past. On the other hand, the tolerance range based on the relationship between environment and the occurrence of ecosystems may not totally represents the true range, considering the influence of anthropic activities. These uncertainties may reduce the applicability of acquiring response curves by satellite data and ancillary data. Nevertheless, if the long-term satellite is available, eliciting satellite data and ancillary data have great potential to construct the response curve of ecosystems to the environment where the information of response curves is limited.

5.2. Evaluating the case study and corresponding measurements

The status of natural forests in the future will be more serious than that in the past and present, especially at the scenario pathway RCP 8.5. This is due to the future temperature in Xishuangbanna being much higher than that in the past and present, far exceeding the optimum range of natural forest (Fig. 6, Table 2, Appendix S5), and forest may potentially suffer heat stress. With higher emission scenarios, the relative severity of natural forest greatly increased. The significantly increased temperatures and slight increase in rainfall may potentially shift the bioclimatic zone in Xishuangbanna (Fig. 10) (Zomer et al., 2014). The shifted bioclimate may not suitable for the original vegetation which may cause risk to the natural forest in Xishuangbanna, as the adaption of vegetation ecosystems are always lag behind the effects

Table 2
The PRS of each natural forest in the past, present and future, as well as their status.

Type	1965a		2015a		2060s (RCP2.6)		2060s (RCP4.5)		2060s (RCP6.0)		2060s (RCP8.5)	
	PRS	ST	PRS	ST	PRS	ST	PRS	ST	RS	ST	PRS	ST
Castanopsis fargesii	3.1%	LC	0.9%	LC	5.7%	LC	9.8%	LC	4.6%	LC	21.4%	LC
Bombax malabaricum	16.7%	LC	7.6%	LC	6.1%	LC	8.6%	LC	5.1%	LC	15.7%	LC
Terminalia myriocarpa	7.9%	LC	1.9%	LC	11.5%	LC	18.3%	LC	9.2%	LC	34.3%	NT
Parashorea chinensis	7.7%	LC	1.1%	LC	19.5%	LC	27.9%	LC	16.4%	LC	45.1%	VU
Semecarpus reticulata	7.5%	LC	2.1%	LC	10.0%	LC	16.2%	LC	8.1%	LC	33.0%	NT
Dendrocalamus strictus	7.4%	LC	1.3%	LC	12.0%	LC	18.4%	LC	9.7%	LC	34.2%	NT

The "ST" mean the status.

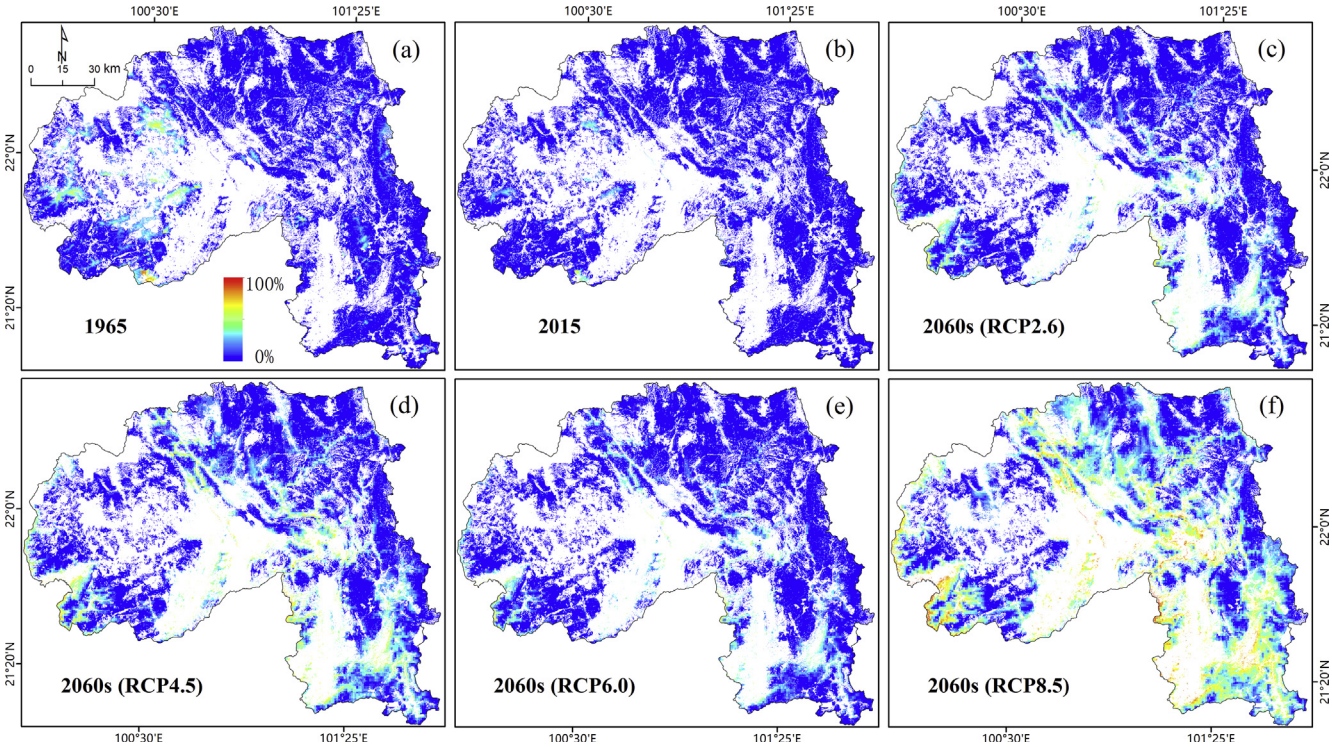

Fig. 7. The spatial distribution of PRS of natural forest in the past, present and future. The mean value of PRS is 3.7% in the past (a), 1.1% in present (b), 6.4% in the future at RCP2.6 (c), 10.8% in the future at RCP4.5 (d), 5.2% in the future at RCP6.0 (e), 22.9% in the future at RCP8.5 (f).

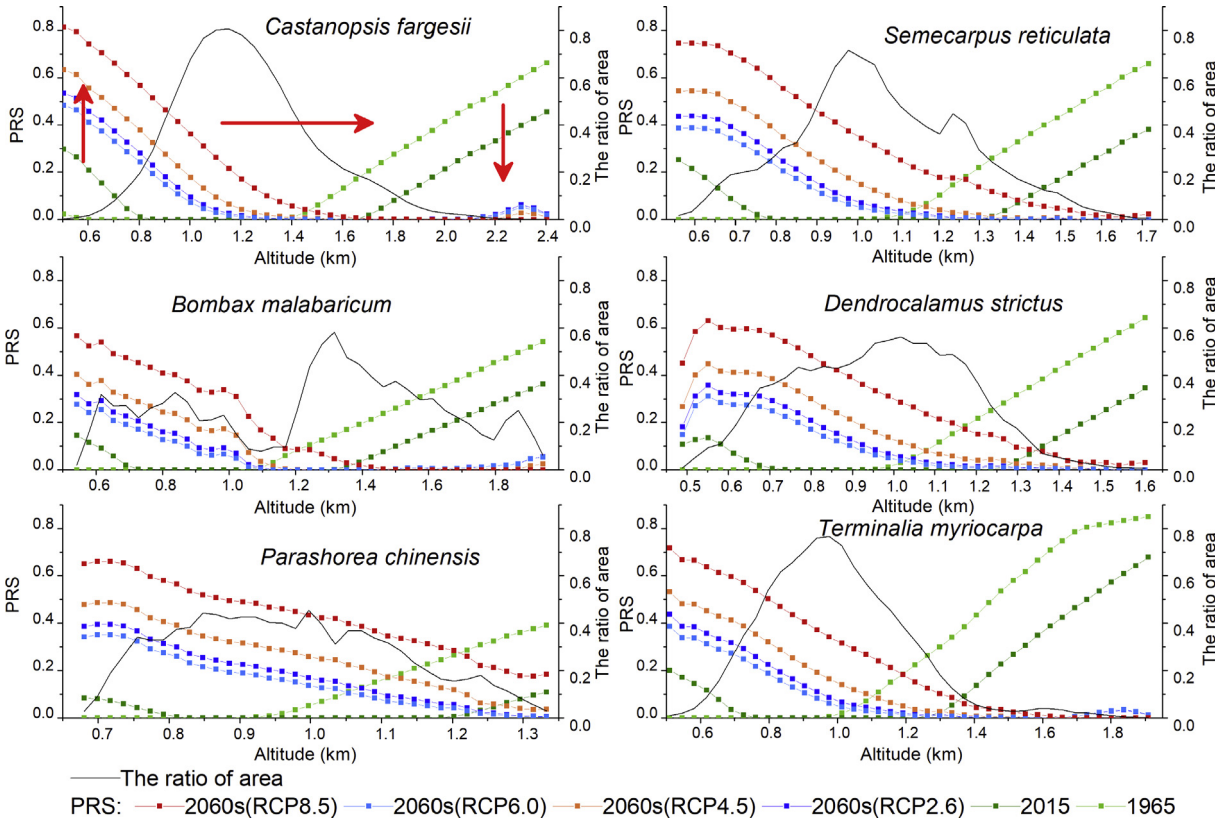

Fig. 8. The altitudinal distribution of PRS for each forest type in the past (1965), present (2015) and future (in 2060s across RCP 2.6, 4.5, 6.0 and 8.5) (left y-scroll). The black line is the histogram of the area of each forest along with altitude gradient (right y-scroll).

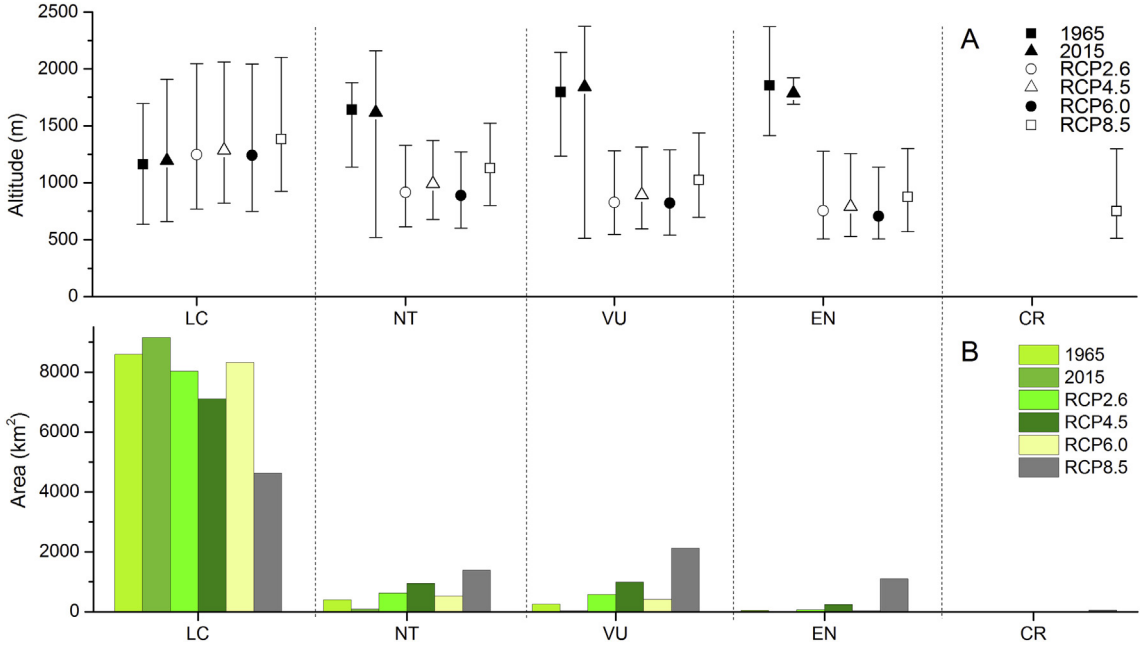

Fig. 9. The elevation of each status in the past (1965), present (2015) and future (in 2060s across RCP 2.6, 4.5, 6.0 and 8.5) (A), as well as the histogram of area of each status in the past, present and future (B). The × axis is the status of ecosystems which referenced the categories in the IUCN Red List of Ecosystem, including Least Concern (LC), Near Threatened (NT), Vulnerable (VU), Endangered (EN), and Critically Endangered (CR). The error bar in plot A indicates the range of variability for the minimum, mean and max elevation ranges of each status.

of climate changes (Corlett and Westcott, 2013). Although the relative severity in the future vary with different RCPs and the overall status of ecosystems are no-threats, the PRS of all scenarios indicate an increase in ecological risk in the future, which could lead to biodiversity loss in Xishuangbanna (Prieto-Torres et al., 2016; Zhao and Running, 2010).

The public and policy makers should pay attention to the abiotic conditions of natural forests in Xishuangbanna in conjunction with climate warming. The impacts of temperature warming on *Terminalia myriocarpa* and *Parashorea chinensis* forest, inhabiting threatened species (Wang, 2004), may potentially increase in the future which should be paid more attention and prioritized for management action because of its limited distribution. Through the distribution of relative severity of each natural forest (Appendix S6), iterative filed observation and measurement should be efficiently and timely taken into the threated patches. Corresponding measures for soil and water conservation in this region should be recommended to improve the ability of threated natural forest to adapt water deficient resulting from heat stress.

Considering the complexity of ecosystems, there are many abiotic factors that synchronously take effects on ecosystems. In addition, the relationship among abiotic variables are significant and unclear. These complexities may challenge the determination of abiotic variables for assessment (Niinemets and Valladares, 2008). In this study, annual mean temperature was assigned as the key environment variable. This does not annual mean temperature is the only one abiotic factor that determine the status of the natural forest in Xishuangbanna. However, the annual mean temperature may play important and direct role in shifting the bioclimatic zone because of its significant changes in the future. Even though temperature hardly represents all the abiotic risk to

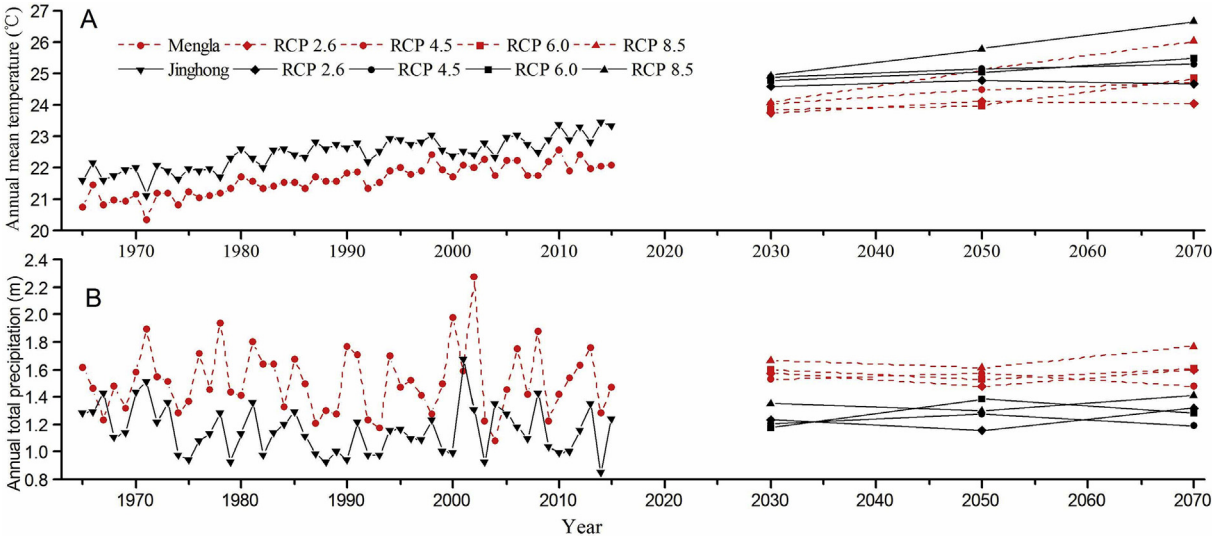

Fig. 10. The annual mean temperature and total precipitation of metrological station in study area from 1965 to 2015 and 2070 (across four RCPs). Plot A is the annual mean temperature which indicates a significant increase, plot B is the annual total precipitation which indicates a slight or rare increase.

natural forest in Xishuangbanna, the result of the ecosystems assessment is consistent with other conclusions and seems reasonable indicating the feasibility of the proposed method. The proposed method also provides a reference for assessing the abiotic degradation of ecosystems in the IUCN Red List of Ecosystems protocol.

5.3. Future work

The method represents an available and consistent way for ecological risk assessment of abiotic stress. Constructing scientific response curves of ecosystems to environment and clarifying the relationship between environmental factors require further exploration. To explicitly indicate the risk of different abiotic factors, the VPD, normalized difference water index (NDWI) and other vegetation indices, derived from satellite data and directly indicating the status of ecosystems to abiotic factors, should be used as the performance of the response curve. The effects of each abiotic variables in determining the degradation of ecosystems may be acquired by calculating the coefficient of determination between the changes in the performance of ecosystems and variation of abiotic variables. More experiments and observations are emergently required to supplement the theory of the response curve of ecosystems to the environment. With the development of remote sensing, ground field observations and ecological models, a more scientific way acquiring response curve of ecosystems to the environment will be available, which would greatly support this method (Wulder et al., 2016).

6. Conclusions

The response curve approach has been recognized by general ecological interest and have a great potential in ecosystem risk assessment. In this study, we elicited a general and direct ecological risk assessment index representing the risk of environmental degradation to ecosystems based on a novel response curve approach and remotely sensed data. Although there are some limitations in the proposed method, the case study in Xishuangbanna indicates the feasibility of the proposed method. Considering that almost all ecosystems have their own response curves to various abiotic factors and the parameters across different response curves are characterized with same ecological meaning, the proposed method will greatly extend the comparability and generality of ecological risk assessment. Based on satellite data and proposed method, the ecological risk assessment can be available in the region where the extent is broad and the information of response curve to environment is limited.

With the development of classic ecological experiment, remote sensing and ecosystem models, the method representing the actual response curve of ecosystems to the environment will be available. The development of these technologies may have great potential to support ecological risk assessment with the proposed method.

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Appendices S1–S6. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2018.11.038.

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